A Comparative Study of Evolutionary Computation Techniques for Solar Cells Parameter Estimation

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Abstract. Recently, the use of renewable energy has attracted the interest of several scientific communities due to the environmental consequences of fossil fuels. Many different technologies have been proposed for the exploitation of clean energies. One of most used is the solar cells considering their unlimited source power characteristics. The estimation of solar cell parameters represents a critical task since its efficiency directly depends on their operative values. However, the determination of such parameters presents several difficulties because of the non-linearity and the multimodal properties from the estimation process. The problem of solar cell parameter estimation has been widely faced through Evolutionary Computation (EC) techniques. Essentially, these methods have produced better results than those obtained by classical methods regarding accuracy and robustness. Each EC algorithm has been designed to fulfill the conditions of specific problems since no one approach can optimize all problems effectively. Under such circumstances, the performance of each EC approach must be correctly assessed considering the application context. Several proposals of EC methods to estimate the parameters of solar cells have been reported in the literature. However, most of them report only a single EC technique considering a minimal number of solar cell models. In this paper, a comparative study of EC techniques used for solar cells parameter estimation is proposed. In the study, the most popular EC approaches currently in use are considered, evaluating their performance over the complete set of solar cell models.

Keywords. Solar cells, evolutionary computational techniques, parameter estimation, three diode model.

1 Introduction

The growing demand and the lack of fossil fuels [1], along with their effects such as air pollution and global warming, have forced to consider alternative energy sources. Solar energy is one of the most promising renewable energy due to its unlimited source of power. Nowadays, the solar photovoltaic energy has attracted the attention in many areas of engineering, increasing its use through the years [2] as a result of its free-emission electrical power generation [3], easy maintenance and availability in isolated areas.

The modeling of solar cells is a complex task attributable to their nonlinear $(I-V)$ behavior and their high dimensionality. Moreover, there exist several factors that adversely affect the modeling of solar cells such as the temperature, the partially shaded conditions [4], just for mention a few. The most efficient method for generating solar cell models is the use of an equivalent electrical system. In the literature, there are two main models reported: the single and the double diode model. The most common configuration is the single diode model which considers five design parameters [5]. On the other hand, the double diode model involves seven design parameters [6] that must be defined. Recent advances in solar cell systems have conducted to the development of more accurate models than those produced by the electronic circuits of one or two diodes. One example of these new models is the configuration of three diodes proposed in [7].

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Under this approach, other important factors of the solar cell can be characterized to improve its operative precision by considering ten different design parameters. Different to other studies, in this paper, the three-diode model is considered for the experimental comparisons.

Several methods have been reported in the literature for the estimation of parameters in solar cells. Some examples involve those based on Newton methods [7], the Lambert functions [8] and least squares [10, 11]. Such techniques can determinate solar cells parameters with a relative good precision; however, they frequently deliver sub-optimal solutions because of their inability to overcome local optima [11].

Evolutionary Computation (EC) techniques are optimization approaches that solve difficult engineering problems due to their efficient search strategies which allow finding optimal solutions. Several EC methods and their variations have been proposed as an alternative to classical techniques for estimating the parameters of solar cells. Essentially, these methods have produced better results than those obtained by classical methods regarding accuracy and robustness. Some examples of such proposals involve Genetic Algorithms (GA) [13, 14], Particle Swarm Optimization (PSO) [15, 16], Artificial Bee Colony (ABC) [17, 18], Differential Evolution (DE) [19, 20], Harmony Search (HS) [21, 22], Cuckoo Search (CS) [23, 24], just for mention a few. However, most of these studies report only a single EC technique considering a minimal number of solar cell models [25-27].

Each EC algorithm has been designed to fulfill the conditions of specific problems since no one approach can optimize all problems effectively. Under such circumstances, the performance of each EC approach must be correctly assessed considering the application context. This paper presents a comparative study of the most popular EC algorithms currently in use for the parameter estimation of single, double and three diode models in solar cells. The techniques considered in the study involve Artificial Bee Colony (ABC) [27], Differential Evolution (DE) [28], Harmony Search (HS) [29], Gravitational Search Algorithm (GSA) [30], Cuckoo Search (CS) [31], Differential Search Algorithm (DSA) [32], the Crow Search Algorithm (CSA) [33], and Covariant Matrix Adaptation with Evolution Strategy (CMA-ES) [35, 36]. The experimental results of this study present the relative performance of each EC technique validated under statistical tests.

This paper is organized as follows; Section 2 presents a brief description of evolutionary computation techniques used in this work. Section 3 details the three equivalent circuit models for the solar cell parameter estimation. In Section 4, the experimental results are reported. In Section 5, the non-parametric statistical tests used for the experimental validation is presented. Finally, in Section 6 the conclusions are discussed.

2 Evolutionary Computation (EC) Techniques

EC techniques are useful tools that allow solving complex problems with a good performance. These algorithms are designed to optimize a set of the task with specific characteristics. Under such circumstances, no one method can solve all problems efficiently. The performance of an EC method is directly determined by the balance between the exploration and exploitation of its optimization process. Therefore, different EC approaches have been developed, where both concepts are specifically combined to produce a particular search strategy. In this section, a brief description of the EC methods used in the comparisons is presented.

2.1 Artificial Bee Colony (ABC)

Artificial Bee Colony was proposed by Karaboga [27] inspired by the behavior of honeybee swarm. The ABC employs a population $\mathbf{S}^k$ $\left(\left\{\mathbf{s}_1^k, \mathbf{s}_2^k, \ldots \mathbf{s}_N^k\right\}\right)$ of N food sources randomly distributed from an initial point $k=0$ to a total number of iterations $k = iterations$. In ABC, each food source $\mathbf{s}_i^k$ $(i \in [1,\ldots,N])$ is represented as a *m*-dimensional vector $\left\{s_{i,1}^k, s_{i,2}^k, \ldots, s_{i,m}^k\right\}$, where *m* is the number of decision variables of the optimization problem. After initialization, the food source quality is evaluated considering a fitness function that determinates if is a feasible solution or not. If the

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solution s_i^k is a candidate, the operators of ABC evolved this candidate to generate a new food source v_i that is defined as follows:

$$v_i = \mathbf{s}_i^k + \phi\left(\mathbf{s}_i^k - \mathbf{s}_j^k\right), \quad i, j \in (1, 2, \ldots, N), \tag{1}$$

where s_j^k is a random food source that satisfies and ϕ is a random scale factor between $[-1,1]$. The fitness function for a minimization problem assigned to a candidate solution can be defined as follow:

$$fit\left(s_i^k\right) = \begin{cases} \dfrac{1}{1 + f\left(s_i^k\right)}, & \text{if } f\left(s_i^k\right) \geq 0, \\ 1 + \text{abs}\left(f\left(s_i^k\right)\right), & \text{if } f\left(s_i^k\right) < 0, \end{cases} \tag{2}$$

where $f(\cdot)$ is the fitness function to be minimized. When a new food source is computed, a greedy selection handle, if the new food source v_i is better than the actual s_i^k, the actual food source s_i^k is replaced for the new one v_i, otherwise the actual food source s_i^k reminds.

2.2 Differential Evolution (DE)

Storn and Price developed Differential evolution algorithm [28], which is a stochastic vector-based evolutionary technique, which utilizes *m*-dimensional vectors defined as follow:

$$\mathbf{x}_i^k = \left(x_{i,1}^k, x_{i,2}^k, \ldots, x_{i,m}^k\right), \quad i = 1, 2, \ldots, N, \tag{3}$$

where $\mathbf{x}_i^k$ is the *i-th* vector at iteration *k.* The DE uses the weighted difference between two vectors to generate a third vector; this process is known as mutation and is described below:

$$\mathbf{v}_i^{k+1} = \mathbf{x}_p^k + F \cdot (\mathbf{x}_q^k - \mathbf{x}_r^k), \tag{4}$$

where F is a constant that controls the magnitude of differential variation within the interval $[0, 2]$. On the other hand, to increment the diversity of the mutated vector, a crossover is incorporated. It is represented as follows:

$$\mathbf{u}_{j,i}^{k+1} = \begin{cases} \mathbf{v}_{j,i} & \text{if} \quad r_i \leq C_r \\ \mathbf{x}_{j,i}^k & \text{otherwise} \end{cases}, \; j = 1, 2, \ldots, d, \; i = 1, 2, \ldots, n, \tag{5}$$

Finally, the vector selection produces the final value comparing the fitness values between the candidate vector against the original as follows:

$$\mathbf{x}_i^{t+1} = \begin{cases} \mathbf{u}_i^{t+1} & \text{if } f\left(\mathbf{u}_i^{t+1}\right) \leq f\left(\mathbf{x}_i^t\right), \\ \mathbf{x}_i^t & \text{otherwise,} \end{cases} \tag{6}$$

2.3 Harmony Search (HS)

Harmony search algorithm was introduced by Geem [29]. This optimization method is particularity based on the improvisation process taking place in jazz music. HS defines a harmony memory with a population of *N* individuals represented as $\mathbf{HM}^k\left(\{\mathbf{H}_1^k, \mathbf{H}_2^k, \ldots, \mathbf{H}_N^k\}\right)$. Each harmony $\mathbf{H}_i^k$ represents a *m*-dimensional vector of the decision variables. After initialization, HS generates new solutions by considering a pitch adjustment or with a random re-initialization.

When a new harmony is produced, a uniform random number between $[0,1]$ is generated r_1, if this number is less than the harmony-memory consideration rate (HMCR), the new harmony is generated with memory considerations, otherwise, the new harmony is re-initialized with random values between bound limits. The generation process of a new harmony is described below:

$$H_{new} = \begin{cases} H_j \in \{x_{1,j}, x_{2,j}, \ldots, x_{HMS,j}\} & \text{with probability HMCR,} \\ lower + (uper - lower) \cdot rand & \text{with Probability (1-HMCR).} \end{cases} \tag{7}$$

To determinate which element should be adjusted by the pitch process, further examinations must be considered. For this operation two parameters are defined: The pitch-adjusting rated (PAR) and bandwidth factor (BW). PAR considers the frequency of adjustment while BW controls the magnitude of the local search process. This complete operation can be described as follows:

$$H_{new} = \begin{cases} H_{new} \pm \text{rand}(0,1) \cdot BW & \text{with probability PAR,} \\ H_{new} & \text{with probability (1-PAR).} \end{cases} \tag{8}$$

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2.4 Gravitational Search Algorithm (GSA)

Rashedi proposed Gravitational Search Algorithm [30] which is based on the laws of gravity. This technique emulates the candidate solutions as masses, which are attacked one each other by the gravitational forces. Under this approach, the quality (mass) of an individual is determined by its fitness value. The GSA uses a population of *N* individuals that represent an *m*-dimensional vector $\mathbf{x}_i^k\left(\left\{\mathbf{x}_1,\mathbf{x}_2,\ldots\mathbf{x}_N\right\}\right)$, where the dimension is the number of decision variables. A force from a mass *i* to a mass *j* in a defined time *t* is determined as follows:

$$F_{ij}^{h}(t) = G(t)\frac{M_{p_i}(t)\times M_{a_j}(t)}{R_{ij}(t)+\varepsilon}(x_j^h(t)-x_i^h(t)), \quad (9)$$

where M_{a_j} is the active gravitational mass related to individual *j*, M_{p_i} is the passive gravitational mass of individual *i*, $G(t)$ is the gravitational constant, ε is a constant, and R_{ij} is the Euclidian distant between *i* and *j* individuals. In GSA, the balance between exploration and exploitation is made by modifying $G(t)$ through the iterations. The sum of all forces acting on individual *i* is expressed bellow:

$$F_i^h(t) = \sum_{j=1,\, j\neq i}^{N} F_{ij}^h(t), \quad (10)$$

the acceleration of each individual at time *t* is given bellow:

$$a_i^h(t) = \frac{F_i^h(t)}{Mn_i(t)}, \quad (11)$$

where Mn_i is the inertia mass of individual *i,* with this, the velocity and position for each individual are computed as follows:

$$\begin{aligned} x_i^h(t+1) &= x_i^h(t) + v_i^h(t+1), \\ v_i^h(t+1) &= \mathrm{rand}()\cdot v_i^h(t) + a_i^h(t). \end{aligned} \quad (12)$$

After evaluating the fitness of each individual, their inertia, and gravitational masses are updated, where a heavier individual means a better solution, fort this, GSA uses the follows equations:

$$Ma_i = Mp_i = M_{ii} = M_i, \quad (13)$$

$$m_i(t) = \frac{f(\mathbf{x}_i(t)) - \mathrm{worst}(t)}{\mathrm{best}(t) - \mathrm{worst}(t)}, \quad (14)$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)}, \quad (15)$$

where are the fitness function and best(*t*) and worst (*t*) represent the best and worst solution of the complete population at time *t.*

2.5 Particle Swarm Optimization (PSO)

Particle Swarm Optimization, introduced by Kennedy [36], is based on the behavior of birds flocking. The PSO uses a group of *N* particles $\mathbf{P}^k\left(\left\{\mathbf{p}_1^k,\mathbf{p}_2^k,\ldots,\mathbf{p}_N^k\right\}\right)$ which after being evaluated by a cost function, the best positions are storage $\mathbf{p}_{i,j}^{*}$. To calculate the velocity of each candidate solution for the next iteration, the following model is used:

$$v_{i,j}^{k+1} = \omega\cdot v_{i,j}^k + c_1\cdot r_1\cdot(p_{i,j}^{*} - p_{i,j}^k) + c_2\cdot r_2\cdot(g_{i,j}^{*} - p_{i,j}^k), \quad (16)$$

where ω is the inertia weighs used to control the velocity $(i=1,2,..,N),(j=1,2,...,p)$. c_1 and c_2 are the acceleration coefficients that adjust the movement of each individual in the positions g and p^{*} respectively. r_1 and r_2 are two random numbers between $[0,1]$. Therefore, to calculate the new position of the individuals used the following equation is employed:

$$p_{i,j}^{k+1} = p_{i,j}^{k} + v_{i,j}^{k+1} \quad (17)$$

Once the new position is computed, it is evaluated by a cost function. If the new solution is better that the last one, then it is replaced, otherwise it remains.

2.6 Cuckoo Search (CS)

The cuckoo search was proposed in 2009 by Deb and Yang [31]. This technique emulates the parasite behavior of cuckoo birds through the use of the Lévy flights [37]. CS uses a population of

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$\mathbf{E}^k(\mathbf{e}_1^k, \mathbf{e}_2^k, ..., \mathbf{e}_N^k)$ individuals (eggs) in a determined number of generations $(N = gen)$, where each individual $\mathbf{e}_i^k$ $(i = 1, 2, ..., N)$ represent a *m*-dimensional vector $\left(\left\{\mathbf{e}_{i,1}^k, \mathbf{e}_{i,2}^k, ..., \mathbf{e}_{i,m}^k\right\}\right)$. To improve the exploration of the search space, CS includes the Lévy flights which perturb each individual with a position c_i using a random step s_i generated with a symmetric distribution computed as follows:

$$s_i = \frac{\mathbf{u}}{|\mathbf{u}|^{1/\beta}}, \tag{18}$$

where $\mathbf{u}\left(\{u_1, u_2, ..., u_n\}\right)$ and $\mathbf{v}\left(\{v_1, v_2, ..., v_n\}\right)$ are *n*-dimensional vectors and $\beta = 3/2$. The elements of $\mathbf{u}$ and $\mathbf{v}$ are calculated by the following normal distribution:

$$u \sim N\left(0, \sigma_u^2\right), \qquad v \sim N\left(0, \sigma_u^2\right), \tag{19}$$

$$\sigma_u = \left(\frac{\Gamma(1+\beta)\cdot \sin(\pi\cdot\beta/2)}{\Gamma(1+\beta/2)\cdot\beta\cdot 2^{(\beta-1)/2}}\right), \qquad \sigma_v = 1, \tag{20}$$

where $\Gamma(\cdot)$ is the Gamma distribution. Once s_i is calculated, c_i is computed as follows:

$$c_i = 0.01 \cdot s_i \oplus \left(e_i^k - e^{best}\right), \tag{21}$$

where $\oplus$ is the element-wise multiplications. Ones are obtained, the new candidate solution is estimated as bellow:

$$e_i^{k+1} = e_i^k + c_i. \tag{22}$$

2.7 Differential Search Algorithm (DSA)

Differential search algorithm [32] imitates the Brownian-like random-walk movement used by an organism to migrate. In the DSA a population $\mathbf{X}^k(\mathbf{x}_1^k, \mathbf{x}_2^k, ..., \mathbf{x}_N^k)$ of individuals (artificial organisms) is initialized randomly through the search space. After the initialization, a *stopover* vector is generated described by the Brownian-like random-walks for each element of the population; this stopover is described below:

$$\mathbf{s}_{i,N} = \mathbf{X}_{i,N} + A\cdot(\mathbf{X}_{ri,N} - \mathbf{X}_{i,N}), \tag{23}$$

where $ri \in [1, NP]$ is a random integer within the population range and $ri \neq i$. A is a scale factor that regulate the position changes of the individuals. For the search process, the stopover position is determined as below:

$$\mathbf{s}'_{i,j} = \begin{cases} \mathbf{s}_{i,j} & \text{if} \quad r_{i,j} = 0, \\ \mathbf{X}_{i,j} & \text{if} \quad r_{i,j} = 1, \end{cases} \tag{24}$$

where $j = [1, .., d]$ and $r_{i,j}$ can take the value of 0 or 1. After the selection of the candidate solution, each individual is evaluated by a cost function $f(\cdot)$ to determinate their quality, then a criterion of selection is used which is described as follows:

$$\mathbf{X}_i^{k+1} = \begin{cases} \mathbf{s}_i^k & \text{if } f\left(\mathbf{s}'_i\right) \leq f\left(\mathbf{X}_i^k\right), \\ \mathbf{X}_i^k & \text{if } f\left(\mathbf{s}'_i\right) > f\left(\mathbf{X}_i^k\right), \end{cases} \tag{25}$$

2.8 Crow Search Algorithm (CSA)

The crow search algorithm was originally proposed by Askarzadeh [33], based on the intelligent behavior of crows. CSA uses a population of $\mathbf{C}^k\left(\left\{\mathbf{c}_1^k, \mathbf{c}_2^k, .., \mathbf{c}_N^k\right\}\right)$ *N* individuals (crows), where each individual represents a *m*-dimensional vector $\left(\left\{\mathbf{c}_{i,1}^k, \mathbf{c}_{i,2}^k, .., \mathbf{c}_{i,m}^k\right\}\right)$. The search strategy of CSA can be summarized in two steps. In the first one, it is when a crow is aware that is being followed for another crow while the second is when is not aware. The states of each crow are determined by a probability factor AP_i^k. Therefore, the new candidate solution is computed as follows:

$$\mathbf{c}_i^{k+1} = \begin{cases} \mathbf{c}_i^k + r_i \times fl \times \left(\mathbf{m}_j^k - \mathbf{c}_i^k\right) & r_j \geq AP_i^k, \\ \text{random position} & \text{otherwise}, \end{cases} \tag{26}$$

where r_i and r_j are random numbers between $[0,1]$, fl is a parameter that controls the flight

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length. $\mathbf{m}_j^k$ is the memory of the crow *j*, which stores the best solution at iteration *k.*

2.9 Covariant Matrix Adaptation with Evolution Strategy (CMA-ES)

CMA-ES [35, 36] is an evolutionary algorithm proposed by Hansen based on the estimation of the covariant matrix on the search data. The CMA-ES uses a population of $\mathbf{X}^k\left(\left\{\mathbf{x}_1^k, \mathbf{x}_2^k, \ldots, \mathbf{x}_N^k\right\}\right)$ *N* individuals, which are randomly initialized. In the each generation, λ individuals are selected to be updated using the following equation:

$$\mathbf{x}_N^{k+1} \sim N\left(\mathbf{x}_w^k, \sigma^{k^2} C^k\right), \tag{27}$$

where $N(\mu, C)$ is a normally distributed random vector with a mean μ and a covariance matrix C. The next weighted mean $\mathbf{x}_w^k$ selected as the best interval is computed as follows:

$$\mathbf{x}_w^k = \sum_{i=1}^{\mu} w_i \mathbf{x}_i^k, \tag{28}$$

where $\sum_{i=1}^{\mu} w_i = 1$. To carry out the modification in the parameters, the CMA-ES uses two different adaptations, on the covariance matrix C^k and on the global step size σ^k. For the covariance matrix adaptation case, an evolution path P_c^{k+1} is used, which depends on the parent's separation with $\mathbf{x}_w^k$ and the recombination points $\mathbf{x}_w^{k+1}$ as is shown below:

$$p_c^{k+1} = \left(1 - c_c\right) P_c^k + H_c^{k+1} \sqrt{c_c\left(2 - c_c\right)} \frac{\sqrt{\mu_{eff}}}{\sigma^k}\left(\mathbf{x}_w^{k+1} - \mathbf{x}_w^k\right), \tag{29}$$

$$\begin{aligned} C_c^{k+1} = {} & \left(1 - c_{\text{cov}}\right) C^k c_{\text{cov}} \frac{1}{\mu_{\text{cov}}} p_c^{k+1}\left(p_c^{k+1}\right)^T + \\ & c_{\text{cov}}\left(1 - \frac{1}{\mu_{\text{cov}}}\right) \sum_{i=1}^{\mu} \frac{w_i}{\sigma(k)}\left(\mathbf{x}_i^{k+1} - \mathbf{x}_i^k\right)\left(\mathbf{x}_i^{k+1} - \mathbf{x}_i^k\right), \end{aligned} \tag{30}$$

$$H_\sigma^{k+1} \begin{cases} 1 & \dfrac{p_\sigma^{k+1}}{1 - (1 - c_\sigma)^{2(k+1)}} < \left(1.5 + \dfrac{1}{n - 0.5}\right) E\left(\left\|N(0, I)\right\|\right), \\ 0 & \text{otherwise}, \end{cases} \tag{31}$$

where $\mu_{eff} = \left(\sum_{i=1}^{\mu} w_i\right)^2 \Big/ \sum_{i=1}^{\mu} w_i$ is the effective variance selection and $c_{\text{cov}} \approx \min\left(1, 2\mu_{eff} / n^2\right)$ is the learning rate. For the global step size adaptation a parallel path is used to modify σ^k, this process is described below:

$$\begin{aligned} p_\sigma^{k+1} = {} & (1 - c_\sigma) p_\sigma^k + \sqrt{c_\sigma(2 - c_\sigma)} B^k \cdot \\ & D^{k^{-1}} B^{k^T} \times \frac{\mu_{eff}}{\sigma^k} \times \left(\mathbf{x}_w^{k+1} - \mathbf{x}_w^k\right), \end{aligned} \tag{32}$$

where B^k is an orthogonal matrix and D^k is a diagonal matrix. The adaptation of global step size for the next generation is given by the following equation:

$$\sigma^{k+1} = \sigma^k \exp\left(\frac{c_\sigma}{d_\sigma}\left(\frac{\left\|p_\sigma^{k+1}\right\|}{E\left(\left\|N(0, I)\right\|\right)} - 1\right)\right), \tag{33}$$

where, $E\left(\left\|N(0, I)\right\|\right) = \sqrt{2}\Gamma\left(n + 1/2\right) / \Gamma\left(n/2\right) \approx \sqrt{n}\left(1 - 1/4n + 1/21n^2\right)$ is the length of p_σ.

3 Modeling of Solar Cells

Solar cells are one of the most essential and increasingly clean energy sources. For this reason, their correct modeling has become an important task nowadays. Several alternatives for the solar cell modeling have been proposed in the literature [38]–[40]. However, the most common models are the equivalent circuits models [5], [6], [41], known as Single diode model (SDM), Double diode model (DDM) and Three diode model (TDM).

3.1 Single Diode Model (SDM)

The single diode model is the basic and most used model for the representation of the solar cell behavior. This model uses a diode connected in parallel with the source of current. Fig. 1 presents a representation of this model. Considering the circuit theory, the total current of single diode model is calculated as follows:

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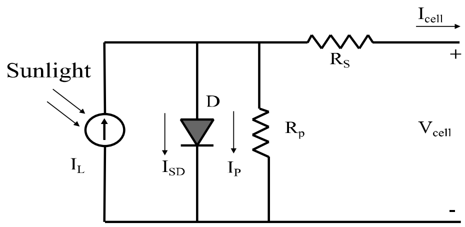

Fig. 1. Single diode model

$$I_{cell} = I_L - I_{SD}\left\{\exp\left[\frac{q\left(V_{cell}+I_{cell}R_S\right)}{nkT}\right]-1\right\} - \frac{V_{cell}+I_{cell}R_S}{R_p}, \quad (34)$$

where k is the Boltzmann constant, q is the electron charge, I_{SD} is the diffusion current, V_{cell} is the terminal voltage, R_p and R_S are the parallel and serial resistances. For the single diode model, the parameters that determinate its performance is given by five parameters; R_S, R_p, I_L, I_{SD} and n.

3.2 Double Diode Model (DDM)

The double diode model is another alternative to characterize the solar cell behavior. Under this circuit, instead of using only one diode, it involves two diodes in a parallel array as is shown in Fig. 2. Therefore, the total current of this model is calculated as follows:

$$I_{cell} = I_L - I_{D1} - I_{D2} - I_p, \quad (35)$$

where the diodes and leakage currents are calculated as follows:

$$I_{D1} = I_{SD1}\left[\exp\left(\frac{q\left(V_{cell}+I_{cell}R_s\right)}{n_1 kT}\right)-1\right], \quad (36)$$

$$I_{D2} = I_{SD2}\left[\exp\left(\frac{q\left(V_{cell}+I_{cell}R_s\right)}{n_2 kT}\right)-1\right], \quad (37)$$

$$I_p = \frac{V_{cell}+I_{cell}R_s}{R_p}. \quad (38)$$

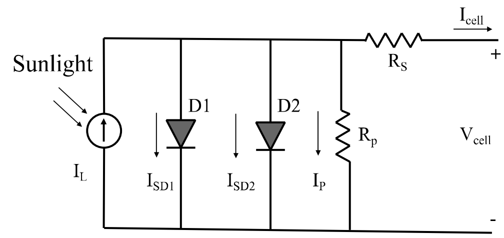

Fig. 2. Double diode model

In the double diode model, the elements that must be determined are R_S, R_P, I_L, I_{SD1}, I_{SD2}, n_1 and n_2.

3.3 Three Diode Model (TDM)

Recent advances in solar cell systems have conducted to the development of more accurate models than those produced by the electronic circuits of one or two diodes. One example of these new models is the configuration of three diodes proposed in [7]. The three diode model is a representation of the solar cell models which include a third diode in parallel with the original two diodes. The model considers the effects of a new current I_{D3} and factor n_3 that allow improving the modeling accuracy. Similarly to the two diode model, the total current is calculated as:

$$I_{cell} = I_L - I_{D1} - I_{D2} - I_{D3} - I_p, \quad (39)$$

$$I_{D1} = I_{SD1}\left[\exp\left(\frac{q\left(V_{cell}+I_{cell}R_{so}\left(1+KI\right)\right)}{n_1 kT}\right)-1\right], \quad (40)$$

$$I_{D2} = I_{SD2}\left[\exp\left(\frac{q\left(V_{cell}+I_{cell}R_{so}\left(1+KI\right)\right)}{n_2 kT}\right)-1\right], \quad (41)$$

$$I_{D3} = I_{SD3}\left[\exp\left(\frac{q\left(V_{cell}+I_{cell}R_{so}\left(1+KI\right)\right)}{n_3 kT}\right)-1\right], \quad (42)$$

$$I_p = \frac{V_{cell}+I_{cell}R_{so}\left(1+KI\right)}{R_p}, \quad (43)$$

In the case of three diode model, the parameter R_s is replaced by $R_{so}\left(1+KI\right)$ to find the variation of R_s with I_{cell}. Where I_{cell} is the load current and K

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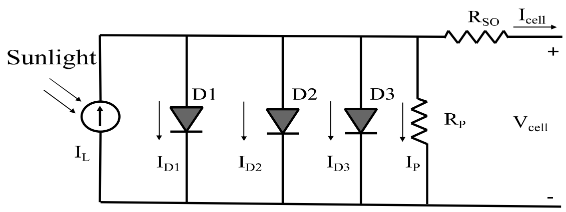

Fig. 3. Three diode model

is a parameter that must be determined as the other parameters, for this, the parameters to be tuned are R_{so}, R_p, I_L, I_{D1}, I_{D2}, I_{D3}, n_1, n_2, n_3 and K.

The solar cells can be configured as modules [42, 43], which are an array of individual solar cells connected in serial and parallel. When the cells are connected to serial the voltages increases N_s times, in the case of cells connected in parallel only the current components increases in N_p times. So that, the output of a module of $N_s \times N_p$ cells is computed as follows:

$$I_m = N_p I_{cell}, \tag{44}$$

$$V_m = N_s V_{cell}, \tag{45}$$

$$R_{sm} = \frac{N_s}{N_p} R_s, \quad R_{pm} = \frac{N_s}{N_p} R_p. \tag{46}$$

3.4 Solar Cells Parameter Identification as an Optimization Problem

The identification of solar cells can be faced as an optimization problem. Under this approach, the objective is the correct approximation of the $I-V$ output between the true model and the equivalent circuit model. With this results, each optimization technique is evaluated by a cost function to determinate the quality of the approximation. For the identification process, the equations (23, 24) and (28) are rewritten to reflex the difference of the experimental data as follows:

$$f_{SDM}(V_{cell}, I_{cell}, \mathbf{x}) = I_{cell} - I_L + I_D + I_p, \tag{47}$$

$$f_{DDM}(V_{cell}, I_{cell}, \mathbf{x}) = I_{cell} - I_L + I_{D1} + I_{D2} + I_p, \tag{48}$$

$$f_{TDM}(V_{cell}, I_{cell}, \mathbf{x}) = I_{cell} - I_L + I_{D1} + I_{D2} + I_{D3} + I_p. \tag{49}$$

For the three models $\mathbf{x}$ represents the parameters to be estimated, for the single diode model (SDM) $\mathbf{x} = [R_s, R_p, I_L, I_{SD}, n]$, in the double diode model (DDM) $\mathbf{x} = [R_s, R_p, I_L, I_{SD1}, I_{SD2}, n_1, n_2]$ and for the three diode model (TDM) $\mathbf{x} = [R_{so}, R_p, I_L, I_{SD1}, I_{SD2}, I_{SD3}, n_1, n_2, n_3, K]$. In order to evaluate the quality of each candidate solution, the root means square error (RMSE) is considered:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (f_i(V_{cell}, I_{cell}, \mathbf{x}))^2}. \tag{50}$$

During the optimization process, the parameters are adjusted to minimize the cost function until a stop criterion is reached. Since the data acquisition is in variant environmental conditions, the objective function presents noisy characteristics and multimodal properties [44]. Under such circumstances, the estimation process is considered as a complex task [45].

4 Experimental Results

For the experiments, an illustrative set of three different solar cell devices have been considered to examine the performance of our approach: the C60 mono-crystalline solar cell (SUNPOWER), the D6P Multi-crystalline Photovoltaic Cell (DelSolar) and KC200GT Photovoltaic Solar Module (Shell Solar). The experimental section consists of three experiments.

In the first experiment, The SUNPOWER solar cell has been used for parameter estimation considering the single and double diode models over different operative conditions. In the second experiment, the DelSolar cell is identified considered the single, double and three diode models. Finally, in the third experiment, the Shell Solar system is identified by using the single and double diode models.

For the Single Diode Model, the number of parameters to be determined is five, in the Double

Table 1. Solar cells parameters ranges for Single, Double, and Three Diode Model

Single Diode Model			Double Diode Model			Three Diode Model		
Parameter	Lower	Upper	**Parameter**	Lower	Upper	**Parameter**	Lower	Upper
$R_s\,(\Omega)$	0	0.5	$R_s\,(\Omega)$	0	0.5	$R_{so}\,(\Omega)$	0	1
$R_p\,(\Omega)$	0	200	$R_p\,(\Omega)$	0	100	$R_p\,(\Omega)$	0	100
$I_L\,(A)$	I_{SC}		$I_L\,(A)$	I_{SC}		$I_L\,(A)$	I_{SC}	
$I_{SD}\,(\mu A)$	0	1	$I_{SD1}\,(\mu A)$	0	1	$I_{SD1}\,(\mu A)$	0	1
n_1	1	2	$I_{SD1}\,(\mu A)$	0	1	$I_{SD2}\,(\mu A)$	0	1
-	-	-	n_1	0	2/3	$I_{SD3}\,(\mu A)$	0	1
-	-	-	n_2	0	2/3	n_1	1	
-	-	-	-	-	-	n_2	2	
-	-	-	-	-	-	n_3	0	3
-	-	-	-	-	-	K	0	1

Diode Model 7 and for the Three Diode Model 10. It is important to remark that the three Diode Model involves three fixed parameters [46]. In the three diode model, I_{SC} is the short circuit current and R_s is also replaced with $R_{so}\,(1+KI)$ to find the variation of R_s respect to the current I. The lower and upper solar cells parameters ranges for each model are shown in Table 1.

In the experiments, each algorithm is compared regarding its estimation accuracy. The methods considered in the comparison are the Artificial Bee Colony (ABC), Crow Search Algorithm (CSA), Cuckoo Search (CS), Differential Evolution (DE), Differential Search Algorithm (DSA), Gravitational Search Algorithm (GSA), Harmony Search (HS), Particle Swarm Optimization (PSO) method [12], and the Co-variance Matrix Adaptation Evolution Strategies (CMA-ES).

These methods are considered as the most popular EC algorithms currently in use. The parameter setting of each EC method for the experimental analysis is defined according to its own references which have demonstrated through experimentation produce the best optimization results. Such configurations are summarized below:

1. ABC: $\text{limit} = 100$, by using [16].
2. CSA: $AP = 0.1$ and $fl = 2$.
3. CS: $p_a = 0.25$ in concordance with [23].
4. DE: $F = 0.4$ and $C_r = 0.4$ [47].
5. DSA: $p_1 = 0.3$ and $p_2 = 0.3$ according to [32].
6. GSA: $G_0 = 100$ and $\alpha = 20$ [30].
7. HS: $HMRC = 0.95$ and $PAR = 0.3$ [22].
8. PSO: $c_1 = 0.5,\ c_2 = 2.5$, the weight factor *w* decreases from 0.9 to 0.4 according to [48].
9. CMA-ES: The parameters are configured according to [34, 35].

In the study, two performance indexes are compared: the root means square error (RMSE) and standard deviation after 40 individual executions. The first index evaluates the accuracy of the algorithm whereas the latter measures its robustness.

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Table 2. Solar cells (Mono-crystalline C60) parameters estimation, Mean and Standard deviation for the Single Diode Model (SDM) and Double Diode Model (DDM) at 1000 W/m^2

SDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
RS (Ω)	0.005065	0.006535176	0.00168	0.00466	0.0051363	0.00542089	0.00920948	0.0034763	0.00662421
Rp (Ω)	183.463	114.252273	199.3241	199.4603	152.35831	79.83066	164.621448	39.481739	200
IL (A)	6.240779	6.21459738	6.546991	6.23187	6.2295673	3.53701901	6.41504223	6.2343094	6.21432845
ID (A)	2.08E-06	2.79016E-07	6.27E-08	3.3E-06	2.197E-06	2.4077E-06	5.3421E-06	3.595E-06	2.41E-07
n	1.697168	1.496370914	1.345742	1.7507	1.7033435	1.87810036	1.82172571	1.7523015	1.48357172
Min RMSE	0.010921	0.009935587	0.267794	0.010551	0.0099479	0.03315632	0.01324157	0.0113077	**0.00992256**
Max RMSE	0.014243	0.01156138	0.268449	0.012094	0.0115475	0.20423651	0.07939054	0.0369322	**0.0104022**
Average RMSE	0.011869	0.010522777	0.268275	0.011191	0.0106624	0.1058941	0.02830248	0.0169241	**0.00995462**
Std	0.00066	0.000461744	0.000122	0.000316	0.0004252	0.04410207	0.01343111	0.0047521	**0.00010586**

DDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
RS (Ω)	0.005678	0.006503674	0.002098	0.006623	0.006368	4.6383E-05	0.00585544	0.0058646	6.62E-03
Rp (Ω)	104.5934	191.2923658	188.4067	135.4169	161.64551	89.7438772	23.2336847	70.063423	2.00E+02
IL (A)	6.226711	6.214465293	6.54696	6.216998	6.2162283	3.29376151	6.09719654	6.2251079	6.21432845
ID1 (A)	2.52E-06	2.98848E-09	6.48E-07	1.29E-06	2.551E-07	3.5163E-06	8.3191E-07	8.32E-07	2.41E-07
ID2 (A)	1.01E-06	2.86929E-07	2.73E-08	1.91E-07	1.984E-07	9.9952E-07	9.2192E-07	5.353E-07	4.16E-16
n1	2.996087	1.548379914	1.936987	2.13222	1.4991135	1.96725788	1.7084817	1.8053035	1.48357169
n2	1.619807	1.499321137	1.290596	1.466079	1.6776963	1.90130136	1.66715067	1.5634685	1.48324541
Min RMSE	0.010186	0.009922907	0.267669	0.009963	0.0099278	0.01742442	0.01243733	0.0104161	**0.00992256**
Max RMSE	0.011947	0.021592727	0.26857	0.03142	0.0309824	0.05321138	0.04337821	0.0137103	**0.01167399**
Average RMSE	0.010878	0.018137755	0.268162	0.014355	0.0128385	0.03266309	0.01869163	0.0115566	**0.00994816**
Std	0.000528	0.000230786	**0.000189**	0.000341	0.0002764	0.00833028	0.00624268	0.0008043	0.00124354

Table 3. Solar cells (Mono-crystalline C60) parameters estimation, Mean and Standard deviation for the Single Diode Model (SDM) and Double Diode Model (DDM) at 800 W/m^2

SDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
RS (Ω)	0.000488	0.000804375	2E-05	0.000608	0.0009882	0.00513349	0.00031329	0.0206406	0.00163057
Rp (Ω)	120.7382	98.41301429	192.0449	199.9999	131.57376	105.754974	77.0013758	66.393912	24.8933861
IL (A)	4.882213	4.881234281	5.130919	4.878856	4.8774982	3.76620098	4.70079256	4.8472653	4.88245696
ID (A)	2.15E-06	1.80815E-06	2.96E-09	2.12E-06	1.464E-06	2.9701E-06	3.8413E-06	6.636E-06	6.87E-07
n	1.728899	1.709113752	1.170159	1.727269	1.684991	1.85447388	1.80017479	1.8717672	1.60471698
Min RMSE	0.004947	0.004868946	0.490195	0.004944	0.004869	0.01796734	0.00803614	0.0059932	**0.00486895**
Max RMSE	0.006511	0.00633468	0.490546	0.005489	0.0051846	0.16861586	0.0824437	0.0320081	**0.0050412**
Average RMSE	0.005311	0.005094385	0.490393	0.005165	0.0049925	0.08699095	0.02791164	0.0169787	**0.00487734**
Std	0.000262	0.000331104	7.47E-05	0.000131	7.706E-05	0.03347491	0.01654392	0.0070283	**3.0309E-05**

DDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
RS (Ω)	0.001232	0.001737993	4.04E-05	0.001437	0.0012232	0.00013346	0.00077359	0.0005271	0.00163057
Rp (Ω)	119.4226	74.60410516	192.1913	31.65655	92.170396	94.7860962	38.135595	54.42826	24.8933897
IL (A)	4.87627	4.876536455	5.130963	4.880101	4.8766252	2.94761087	4.87654863	4.8827055	4.88245696
ID1 (A)	1.33E-06	1.72118E-06	6.3E-10	1.25E-06	7.495E-07	1.1397E-06	5.4769E-06	1.97E-06	4.12E-20
ID2 (A)	0.004192	2.67912E-07	1.94E-08	6.06E-07	4.097E-07	9.9984E-07	2.4922E-07	3.501E-07	6.87E-07
n1	1.674555	1.920364455	1.090282	2.045905	1.6671119	1.9393706	1.89673872	1.7292267	1.96919786
n2	51.2116	1.533094915	1.999292	1.598242	1.6469724	1.81085015	1.65114007	1.812426	1.60471696
Min RMSE	0.004884	0.004870705	0.489958	0.004879	0.00487	0.01021258	0.00666149	0.0049378	**0.00486895**
Max RMSE	0.005309	0.005923922	0.490594	0.005059	0.0053881	0.03878291	0.02295133	0.0077401	**0.00505602**
Average RMSE	0.005044	0.004957579	0.490274	0.004934	0.0050934	0.02353969	0.01157486	0.0057249	**0.00491157**
Std	0.000144	0.000171857	0.000156	3.71E-05	0.0001448	0.00730923	0.00383631	0.0008088	**3.6698E-05**

Table 4. Solar cells (Mono-crystalline C60) parameters estimation, Mean and Standard deviation for the Single Diode Model (SDM) and Double Diode Model (DDM) at 500 W/m^2

SDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
RS (Ω)	0.0016	0.003883448	1.17E-05	0.003187	0.0039048	0.00821181	0.00642602	0.4181931	0.00441815
Rp (Ω)	163.4687	199.973256	198.2291	200	130	115.937296	109.512364	168.0123	48.9235971
IL (A)	3.038953	3.037506852	3.364666	3.039108	3.0385235	1.59703402	3.09297001	3.0363817	3.04073716
ID (A)	2.33E-06	7.66902E-07	4.89E-11	1.16E-06	7.455E-07	8.4011E-07	7.4442E-06	1.78E-06	4.93E-07
n	1.769269	1.640749248	1.006255	1.685994	1.6376616	1.94585248	1.93745184	1.7383762	1.59453154
Min RMSE	0.004097	0.003977713	0.775675	0.004006	0.0039789	0.00621321	0.00573558	0.0043468	**0.00397771**
Max RMSE	0.004518	0.00485107	0.775887	0.004348	0.0043833	0.05531805	0.03164257	0.0079782	**0.00404263**
Average RMSE	0.004288	0.00408547	0.775706	0.004139	0.0040739	0.03202631	0.01165965	0.0055138	**0.00398091**
Std	9.52E-05	0.000195093	3.73E-05	8.61E-05	9.076E-05	0.01185082	0.00541076	0.0009191	**1.2258E-05**

DDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
RS (Ω)	0.004034	0.004177475	7.24E-05	0.003613	0.0041682	0.00056852	6.1811E-05	0.0009983	0.00441815
Rp (Ω)	77.26164	53.46679376	199.3801	190.1412	76.437153	83.6005286	105.243007	193.65696	48.9235809
IL (A)	3.045323	3.03984558	3.364619	3.03873	3.0393953	1.84818457	3.0452358	3.0414082	3.04073717
ID1 (A)	6.91E-07	3.52681E-06	6.22E-11	8.18E-07	7.987E-10	1.8939E-06	5.2676E-06	3.468E-06	4.93E-07
ID2 (A)	0.000382	6.38146E-08	1.01E-10	5.59E-07	5.927E-07	9.9958E-07	6.8983E-07	9.414E-07	2.05E-20
n1	1.630061	1.995274001	1.63944	1.950576	1.7433395	1.98517022	1.88922847	1.9159403	1.59453153
n2	30.69521	1.439759222	1.03605	1.617409	1.6134584	1.91104148	1.99442602	1.7420063	1.9973227
Min RMSE	0.003986	0.003977746	0.775707	0.003984	0.003978	0.00519559	0.00485494	0.0040001	**0.00397771**
Max RMSE	0.004303	0.00445058	0.776099	0.004639	0.0041926	0.01890252	0.01283665	0.0046005	**0.00407281**
Average RMSE	0.004106	0.004025824	0.775866	0.004214	0.0040236	0.01149578	0.00692778	0.00416	**0.00402082**
Std	0.000113	9.35314E-05	9.82E-05	**2.21E-05**	5.435E-05	0.0032242	0.00151241	0.0001555	0.00016829

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Table 5. Solar cells (Mono-crystalline C60) parameters estimation, Mean and Standard deviation for the Single Diode Model (SDM) and Double Diode Model (DDM) at 300 W/m^2

SDM

Parameters	ABC	CSA	CS	DE	DSA	GSA	HS	PSO	CMA-ES
RS (Ω)	0.022856	0.024935901	1.28E-07	0.021591	0.019553	0.0057405	0.01079812	0.0157213	0.03784345
Rp (Ω)	89.60072	96.99719894	199.9309	200	196.57055	95.1381775	117.815101	198.31323	20.3660429
IL (A)	1.815495	1.799703082	2.16471	1.804586	1.8048883	0.647616	1.81085624	1.8076504	1.8066546
ID (A)	6.67E-07	1.66103E-07	1.75E-11	6.07E-07	1.356E-06	2.2364E-08	4.8415E-06	4.25E-06	4.88E-11
n	1.680349	1.537152887	1.000012	1.669162	1.7645843	1.97885237	1.93524352	1.9192075	1.02519908
Min RMSE	0.005007	0.004163427	0.972854	0.004777	0.0041294	0.00669648	0.00603242	0.0050737	**0.00324028**
Max RMSE	0.00604	0.005120555	0.972854	0.005612	0.0055624	0.02650582	0.0148986	0.0069059	**0.00484652**
Average RMSE	0.005533	0.004597845	0.972854	0.005207	0.0049094	0.01435318	0.00831713	0.0059562	**0.00364383**
Std	0.000167	0.000266064	**7.89E-08**	0.000162	0.0003	0.00500556	0.00195439	0.0003223	0.00060098

DDM

Parameters	ABC	CSA	CS	DE	DSA	GSA	HS	PSO	CMA-ES
RS (Ω)	0.019759	0.009998557	1.11E-06	0.019881	0.0099999	0.00294815	0.00572879	0.0049867	0.03453452
Rp (Ω)	108.4338	190.951882	198.7353	199.9866	199.49798	89.6325187	29.6722844	60.11981	1.28E+02
IL (A)	1.808202	1.801598482	2.164701	1.806197	1.8026873	1.64108059	1.79601671	1.7960872	1.80E+00
ID1 (A)	1.4E-06	5.36334E-06	1.3E-09	1.12E-06	6.436E-06	2.6725E-06	2.3832E-06	5.283E-06	2.87E-08
ID2 (A)	9.51E-07	9.9852E-07	1.77E-11	6.06E-07	9.032E-07	9.8344E-07	7.7925E-07	5.803E-07	1.12E-09
n1	1.767764	1.999925106	1.941844	1.744111	1.9999988	1.97590137	1.8494644	1.968805	1.85070386
n2	4.789302	1.892108949	1.0004	2.260392	1.999976	1.81370144	1.96612708	1.9296981	1.18E+00
Min RMSE	0.004836	0.00683517	0.972855	0.004646	0.0068351	0.0076357	0.00749499	0.0069709	**0.00349494**
Max RMSE	0.00596	0.007264676	0.972864	0.005748	0.0068425	0.01570402	0.01230902	0.0075616	**0.00573986**
Average RMSE	0.005606	0.006895311	0.972859	0.005281	0.0068354	0.01074707	0.00871806	0.0071482	**0.00489288**
std	0.000299	8.98654E-05	2.38E-06	0.000227	**1.212E-06**	0.00152859	0.00095817	0.0001411	0.0005975

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Table 6. Solar cells (Mono-crystalline D6P) parameters estimation, Mean and Standard deviation for the Single Diode Model (SDM), Double Diode Model (DDM) and Three Diode Model (TDM) at 1000 W/m^2

SDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
RS (Ω)	4.93E-03	0.00550083	0.006453	0.005662	0.005988	0.005038	0.001861	0.4709873	0.47098731
Rp (Ω)	7.50E+01	100	99.45801	100	99.99615	66.07779	80.98159	57.768198	57.7681979
IL (A)	8.31E+00	8.30252074	8.299179	8.300678	8.294515	6.897731	8.23392	8.2149683	8.21496834
ID (A)	1.57E-06	5.34E-07	6.53E-08	3.51E-07	1.64E-07	1E-05	7.31E-06	8.249E-06	8.2489E-06
n	1.606934	1.50376702	1.335087	1.466456	1.404038	1.90333	1.776386	1.7966804	1.79668045
Min RMSE	0.023204	0.02320388	0.015645	0.019481	0.019044	0.034982	0.034982	0.0260146	**0.01552954**
Max RMSE	0.025538	0.02553847	0.023851	0.023045	0.024382	0.216904	0.216904	0.0447331	**0.02003157**
Average RMSE	0.024574	0.02457448	0.019163	0.020916	0.021132	0.108073	0.108073	0.0311407	**0.01892337**
Std	**0.00069**	0.00068966	0.002722	0.000794	0.001218	0.047229	0.047229	0.0036418	0.00082729
DDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
RS (Ω)	5.70E-03	0.00555699	0.006699	0.006064	0.006557	0.002284	0.003773	0.0041813	0.00418127
Rp (Ω)	6.71E+01	100	89.09031	100	99.96804	35.31513	55.90306	79.052877	79.0528766
IL (A)	8.29E+00	8.30146867	8.281023	8.296526	8.288297	7.172523	8.287227	8.3190704	8.31907043
ID1 (A)	3.82E-06	3.92E-07	3.55E-08	1.57E-07	1.71E-10	3.94E-06	4.96E-06	4.837E-06	4.8375E-06
ID2 (A)	2.48E-07	4.30E-07	2.22E-11	1.8E-07	4.63E-08	1E-06	9.89E-07	1.198E-08	1.198E-08
n1	5.71E+00	1.88991907	1.293362	23.35675	1.176865	1.86705	1.770647	1.7332564	1.73325637
n2	1.438037	1.48667571	1.389624	1.412048	1.313473	1.62115	1.712209	1.8487766	1.84877659
Min RMSE	0.02146	0.02146031	0.017369	0.019226	0.017316	0.029422	0.029422	0.0215297	**0.01707178**
Max RMSE	0.025601	0.02560146	0.027343	0.023371	0.02305	0.06036	0.06036	0.0281581	**0.02145989**
Average RMSE	0.023643	0.02364294	0.024494	0.021652	0.020183	0.039861	0.039861	0.0252211	**0.01940024**
Std	0.001206	0.0012056	0.002065	0.001091	0.001305	0.00789	0.00789	0.0016887	**0.00098192**
TDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
ID1 (A)	1.21E-10	1.177E-10	1.21E-10	8.59E-26	1.21E-10	1.23E-10	1.24E-10	1.249E-08	1.2486E-08
ID2 (A)	8.23E-11	2.1463E-07	2.13E-13	3.31E-05	3.82E-21	9.20E-13	7.97E-07	2.312E-07	2.3123E-07
ID3 (A)	4.92E-04	9.9377E-06	1.2E-15	2.52E-19	3.14E-14	2.33E-10	8.69E-06	7.016E-06	7.0156E-06
n3	8.80E+01	2.41406574	0.863338	2.993156	98.52522	2.996657	2.97427	2.6504631	2.65046313
Rso (Ω)	8.02E-03	0.00738269	0.008045	0.002745	0.008045	0.008008	0.005064	0.0063443	0.00634432
K	6.74E-04	0.01435204	9.35E-09	1.74E-16	1.91E-15	0.004806	0.016666	0.0474956	0.04749557
Rsh (Ω)	1.84E+00	2.12835817	1.819064	4.077476	1.818718	99.99369	36.85799	69.683667	69.6836673
Min RMSE	0.020393	0.02039341	0.020388	0.020393	0.019618	0.023934	0.062702	0.0262095	**0.01949509**
Max RMSE	0.020471	0.02047111	0.020393	0.020393	0.03713	0.0333	39.09412	0.0550369	**0.02038819**
Average RMSE	0.020404	0.02040431	0.020393	0.020393	0.025195	0.0535	9.684074	0.0400163	**0.02010918**
Std	1.62E-05	1.6213E-05	9.3E-07	**5.66E-09**	0.00665	0.000455	8.682488	0.0052987	0.00028239

Table 7. Solar cells (Mono-crystalline D6P) parameters estimation, Mean and Standard deviation for the Single Diode Model (SDM), Double Diode Model (DDM) and Three Diode Model (TDM) at 500 W/m^2

SDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
RS (Ω)	0.004157	0.01159328	2E-09	0.005909	0.00681	0.001227	0.000849	0.0029151	0.00749966
Rp (Ω)	69.17906	100	99.99913	100	99.99975	35.77021	94.14903	43.577466	100
IL (A)	4.156335	4.13161166	4.6471	4.142898	4.141783	2.647298	4.202613	4.1544498	4.140932
ID (A)	1.49E-06	2.27E-10	7.22E-11	3.12E-07	1.51E-07	7.05E-06	9.55E-06	3.263E-06	7.25E-08
n	1.586101	1	1.000001	1.435838	1.376114	1.933243	1.807051	1.6732462	1.31973729
Min RMSE	0.017136	0.01713641	0.567476	0.016359	0.015404	0.018751	0.018751	0.017759	**0.01416909**
Max RMSE	0.018008	0.01800797	0.567477	**0.017199**	0.017287	0.076983	0.076983	0.0188433	0.01740387
Average RMSE	0.017607	0.01760732	0.567476	0.016775	0.016542	0.043495	0.043495	0.0183816	**0.01611262**
STD	0.000187	0.00018661	**8.51E-08**	0.00021	0.000376	0.013287	0.013287	0.0002893	0.00111236
DDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
RS (Ω)	6.51E-03	0.00711864	7.29E-05	0.005624	0.006064	0.00253	0.004874	0.0055739	0.00557385
Rp (Ω)	7.98E+01	100	99.91123	100	61.38597	49.47878	82.65916	82.816173	82.816173
IL (A)	4.16E+00	4.14223473	4.646989	4.144588	4.144383	4.158399	4.146255	4.1468956	4.14689559
ID1 (A)	8.07E-07	1.19E-07	8.61E-11	1.59E-06	2.08E-07	4.32E-06	9.28E-07	7.139E-06	7.1389E-06
ID2 (A)	1.87E-07	9.57E-08	9.06E-10	1.32E-07	9.99E-07	9.94E-07	8.06E-07	3.587E-07	3.5869E-07
n1	3.66E+01	1.35906364	1.007153	1.800635	1.404134	1.81406	1.980265	1.5796227	1.5796227
n2	1.392767	1.77294891	1.950849	1.380061	1.999837	1.603871	1.528525	1.4499956	1.44999562
Min RMSE	0.015887	0.01588696	0.567477	0.016084	0.01645	0.017171	0.017171	0.0165929	**0.01519835**
Max RMSE	0.017786	0.01778611	0.567613	**0.017333**	0.018129	0.019554	0.019554	0.0174407	0.01735582
Average RMSE	0.017235	0.01723534	0.567503	0.016818	0.017597	0.018417	0.018417	0.017041	**0.01624427**
std	0.000408	0.000408	**2.78E-05**	0.000279	0.000373	0.000565	0.000565	0.0002042	0.00048383
TDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
ID1 (A)	2.10E-10	2.1006E-10	1.58E-13	1.55E-10	6.72E-11	1.21E-10	1.65E-10	4.144E-08	4.1445E-08
ID2 (A)	3.24E-15	2.1954E-07	2.93E-10	6.89E-21	6.02E-19	5.47E-07	6.31E-07	4.874E-07	4.8742E-07
ID3 (A)	4.83E-10	3.4658E-11	7.69E-14	1.02E-15	3.12E-13	1.19E-14	9.28E-06	4.896E-06	4.8958E-06
n3	9.32E+01	1.78535981	0.784333	0.684267	0.792991	0.99053	1.945619	2.1120764	2.11207644
Rso (Ω)	1.03E-02	0.00999985	0.001608	0.011271	0.01	0.007961	0.002745	0.0071011	0.00710112
K	4.35E-11	2.4762E-06	0.002556	4.17E-15	0.039095	0.003907	0.098125	0.0547249	0.05472488
Rsh (Ω)	7.10E-01	0.70491482	99.97324	0.707655	0.69295	67.37059	0.632458	70.815981	70.8159813
Min RMSE	0.042226	0.04222615	0.567153	0.042226	0.041832	0.043415	0.089162	0.0439661	**0.04059946**
Max RMSE	0.042227	0.04222669	0.567277	0.042226	0.042156	1.6245	5.652148	0.0800799	**0.04197422**
Average RMSE	0.042226	0.04222618	0.5672	0.042226	0.04195	0.2893	1.757516	0.0592006	**0.04142937**
Std	1.03E-07	1.0326E-07	3.12E-05	**9.81E-18**	0.000115	0.000455	1.565291	0.0102721	0.00034344

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Table 8. Solar cells Module (Multi-crystalline KC200GT) parameters estimation, Mean and Standard deviation for the Single Diode Model (SDM) and Double Diode Model (DDM) at 1000 W/m^2

SDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
RS (Ω)	0.00819725	0.008598412	0.009702	0.008254	0.0085027	0.00532522	0.006372	0.0086455	0.00838946
Rp (Ω)	14.2746543	287.7649217	278.3281	300	274.24082	162.599163	145.730272	70.236383	500
IL (A)	8.45231967	8.401473158	8.395708	8.405986	8.4081122	5.51397782	8.1667034	8.4517976	8.40253114
ID (A)	2.1304E-06	8.80807E-07	1.02E-07	1.24E-06	1.218E-06	4.8699E-06	9.1479E-06	5.298E-06	1.23E-06
n	1.63367968	1.542895531	1.361663	1.575057	1.5744236	1.83695064	1.81751613	1.7462203	1.57520904
Min RMSE	0.00619726	0.005158409	0.006143741	0.006055	0.0051727	0.01676816	0.0077667	0.0071031	**0.00506031**
Max RMSE	0.00819386	0.006852389	0.006919949	0.006854	0.0066646	0.08468712	0.03851485	0.0182919	**0.00594658**
Average RMSE	0.00697368	0.006031249	0.006439478	0.00623	0.0059189	0.05137936	0.01626893	0.0110058	**0.00536039**
Std	0.00051988	0.000375625	0.000262026	0.000192	0.0003831	0.0164289	0.00766401	0.0026008	**0.00013732**
DDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
RS (Ω)	0.01018216	0.010537688	0.010568	0.010349	0.0105334	0.00579965	0.0125366	0.4753595	0.01040301
Rp (Ω)	136.897439	133.9638333	264.3318	299.9873	299.97365	169.410993	245.068672	141.23624	197.337864
IL (A)	8.37444967	8.371571382	8.371119	8.371028	8.3703729	4.12627659	8.01575802	8.074969	8.37548908
ID1 (A)	6.439E-08	2.32597E-15	7.8E-09	1.36E-08	3.258E-13	9.9792E-09	4.8326E-09	2.546E-09	1.15E-10
ID2 (A)	2.2274E-08	8.47844E-09	2.55E-09	2.69E-08	8.692E-09	9.9249E-09	5.1778E-09	1.771E-09	1.25E-08
n1	8.73132142	1.351574739	1.194356	1.227365	1.1265378	1.6933772	1.17566595	1.5137775	1.24036008
n2	1.25726919	1.199160692	1.875205	1.747515	1.2006042	1.89036558	1.51451236	1.1106203	1.22215402
Min RMSE	0.00473273	0.004717362	0.004821636	0.004718	0.0047173	0.01310982	0.00566407	0.0061483	**0.00471767**
Max RMSE	0.00518495	0.004856829	0.004741333	0.004753	0.004756	0.09772879	0.06769827	0.0190041	**0.00472145**
Average RMSE	0.00487024	0.004737393	0.00482412	0.004728	0.0047213	0.05200618	0.0274881	0.0114809	**0.004719**
Std	0.00011032	2.80154E-05	8.61837E-07	8.93E-06	6.524E-06	0.01691836	0.01305747	0.0041682	**7.0567E-06**

Table 9. Solar cells Module (Multi-crystalline KC200GT) parameters estimation, Mean and Standard deviation for the Single Diode Model (SDM) and Double Diode Model (DDM) at 800 W/m^2

SDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
RS (Ω)	0.00560748	7.82E-05	2.84E-05	5.75E-03	1.08E-03	0.00473677	1.76E-03	0.5313321	0.00392955
Rp (Ω)	156.472585	499.9948083	472.2883	500	499.99812	2.86E+02	115.897865	98.146888	500
IL (A)	6.74823457	5.13E+00	5.130815	6.745251	5.131	1.35389938	5.13099889	2.9315738	5.131
ID (A)	3.56E-06	5.16E-09	3.67E-07	2.53E-06	1.80E-08	7.58E-08	4.55E-06	3.48E-06	2.60E-10
n	1.6482632	1.187243554	1.441785	1.610137	1.2151826	1.84E+00	1.71599654	1.7138988	1.00003708
Min RMSE	0.00607673	0.153164765	0.153071491	0.006144	0.1530621	0.15859113	0.15484765	0.1549824	**0.00596914**
Max RMSE	0.00770129	0.154739618	0.153109032	0.006847	0.1532002	0.21342771	0.1611923	0.1601034	**0.00681995**
Average RMSE	0.0069878	0.153856882	0.153088145	0.006439	0.1531086	0.16944026	0.15669185	0.15735	**0.00637779**
Std	0.00037055	0.000400204	**8.81371E-06**	0.00023	3.457E-05	0.01004141	0.00143392	0.0013584	0.00015752
DDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
RS (Ω)	0.00652112	0.002510291	0.004005	0.007576	0.0039691	0.00323222	8.39E-04	2.61E-01	0.00400321
Rp (Ω)	290.306499	471.3428232	499.4977	5.564204	5.00E+02	2.75E+02	2.55E+02	365.18762	500
IL (A)	6.72995842	5.130923625	5.131	6.775167	5.1309999	2.85E+00	5.13E+00	3.89E+00	5.131
ID1 (A)	7.78E-07	1.48E-10	4.82E-10	4.07E-08	2.58E-10	1.96E-10	9.69E-09	6.76E-09	2.57E-10
ID2 (A)	7.30E-07	1.71E-10	2.56E-10	6.39E-08	3.03E-11	9.92E-09	4.43E-09	5.24E-09	8.86E-21
n1	1.49260116	1.014655345	1.787907	1.347456	1.0001267	1.73017437	1.17802325	1.808445	1
n2	50.4069533	1.764172097	1.00E+00	1.317329	1.9897464	1.61841891	1.66892515	1.1611895	1.99938964
Min RMSE	0.00474219	0.153022239	0.152992432	0.004718	0.1529846	0.1550537	0.15346329	0.1534739	**0.00471636**
Max RMSE	0.00535054	0.153360344	0.153025772	0.004818	0.1530329	0.1682246	0.16383126	0.1604568	**0.00475133**
Average RMSE	0.00495841	0.153098018	0.15301046	0.00473	0.1530076	0.1619196	0.15583403	0.1556357	**0.00472412**
STD	0.00016899	6.08071E-05	9.66935E-06	1.58E-05	1.29E-05	0.00284984	0.00231309	0.0015596	**7.5167E-06**

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Table 10. Solar cells Module (Multi-crystalline KC200GT) parameters estimation, Mean and Standard deviation for the Single Diode Model (SDM) and Double Diode Model (DDM) at 600 W/m^2

SDM

Parameters	ABC	CSA	CS	DE	DSA	GSA	HS	PSO	CMA-ES
RS (Ω)	0.00579404	4.69E-06	0.000354	0.00471	1.99E-09	0.02399241	3.23E-04	0.4360552	9.29E-19
Rp (Ω)	103.380418	494.4540364	4.19E+02	11.75391	499.99974	2.75E+02	297.465108	2.40E+02	500
IL (A)	5.03219147	3.364709848	3.36464	5.064251	3.36471	1.52204555	3.36E+00	2.97E+00	3.36471
ID (A)	4.38E-07	5.72E-11	6.08E-08	1.25E-06	4.86E-10	1.76E-09	2.17E-06	2.79E-06	2.61E-10
n	1.43825761	1.00107902	1.320566	1.535283	1.029505	1.926606	1.68277169	1.76E+00	1
Min RMSE	0.00656172	0.240433034	0.240272335	0.006144	0.2402715	0.24175207	0.24147391	0.2415572	**0.00589603**
Max RMSE	0.00937572	0.241981687	0.240302873	0.007021	0.2404957	0.26679805	0.24479858	0.2442355	**0.00681995**
Average RMSE	0.00737129	0.241182992	0.240281109	0.006459	0.2403316	0.24944009	0.24224258	0.2426385	**0.00623948**
Std	0.00064136	0.000392438	**8.22765E-06**	0.000235	5.655E-05	0.00521166	0.00076707	0.0006874	0.00013652

DDM

Parameters	ABC	CSA	CS	DE	DSA	GSA	HS	PSO	CMA-ES
RS (Ω)	0.00663807	1.81E-06	7.46E-06	7.65E-03	5.30E-12	3.95E-03	1.67E-03	0.0156249	6.69E-18
Rp (Ω)	6.47586816	493.0062779	4.80E+02	3.829101	499.99997	2.51E+02	3.67E+02	2.41E+02	500
IL (A)	5.06785663	3.364709691	3.364706	5.10E+00	3.36471	2.08921992	3.36404429	8.69E-01	3.36471
ID1 (A)	1.11E-07	5.25E-11	3.02E-10	2.82E-10	2.61E-10	4.09E-10	6.27E-09	5.54E-09	2.61E-10
ID2 (A)	1.28E-08	5.64E-11	9.76E-09	1.59E-08	5.06E-15	4.18E-10	4.48E-09	4.12E-09	1.69E-20
n1	1.32627965	1.813680317	1.007273	1.287049	1	1.67217836	1.16332975	1.4373337	1
n2	16.9103492	1.000368025	1.772075	1.195659	1.9984145	1.58346052	1.61249948	1.1380601	1.98601177
Min RMSE	0.00474395	0.240326451	0.2402723	0.004719	0.2402715	0.24114319	0.24074788	0.2410345	**0.00471636**
Max RMSE	0.00527847	0.241718986	0.240276037	0.004751	0.2402715	0.24875306	0.24933665	0.2423547	**0.00474795**
Average RMSE	0.00494073	0.240753244	0.240274015	0.004727	0.2402715	0.24357299	0.24184863	0.2417584	**0.00472412**
Std	0.00013252	0.000424668	9.58666E-07	6.2E-06	**2.082E-09**	0.00155382	0.00139945	0.000263	7.8217E-06

In the comparisons, each algorithm is set with 50 individuals.

To eliminate the random effect, each experiment is tested for 40 independent runs. In the comparison, a fixed number of iterations (2000) has been considered as a stop criterion. This stop criterion has been decided to keep compatibility with similar works published in the literature.

4.1 Identification of C60 Mono-Crystalline Solar Cell

The first experiment involves the parameter estimation of a solar cell C60 Mono-crystalline, considering four different sun irradiations: $\left(1000\ \mathrm{W/m^2}\right)$, $\left(800\ \mathrm{W/m^2}\right)$, $\left(500\ \mathrm{W/m^2}\right)$ and

Table 11. Solar cells Module (Multi-crystalline KC200GT) parameters estimation, Mean and Standard deviation for the Single Diode Model (SDM) and Double Diode Model (DDM) at 400 W/m^2

SDM

Parameters	ABC	CSA	CS	DE	DSA	GSA	HS	PSO	CMA-ES
RS (Ω)	0.0082898	8.73E-09	0.00013	0.008543	1.01E-09	8.84E-03	0.00262176	0.4076231	2.47E-16
Rp (Ω)	244.788126	499.9985195	5.00E+02	15.25072	499.99657	226.435541	364.481124	341.52765	5.00E+02
IL (A)	3.37145929	2.164709998	2.164709	3.388371	2.16E+00	1.47930568	2.16E+00	1.1096869	2.16E+00
ID (A)	2.24E-06	1.64E-11	1.04E-08	2.03E-06	4.69E-10	8.90E-09	9.91E-07	1.72E-06	2.43E-10
n	1.61640042	1.000000439	1.20E+00	1.606847	1.029216	1.69801672	1.63653468	1.6495691	1
Min RMSE	0.00645975	0.300912307	0.300845399	0.006144	0.3008454	0.30158912	0.30100127	0.3010593	**0.00543773**
Max RMSE	0.01174902	0.302867207	0.300845464	0.007065	0.3008454	0.32471022	0.3035138	0.3040074	**0.00681995**
Average RMSE	0.00764025	0.301076997	0.300845412	0.006528	0.3008454	0.3082867	0.30152288	0.3023678	**0.00643948**
Std	0.00094938	0.000375184	1.30416E-08	0.000307	**1.585E-15**	0.0050065	0.00053007	0.0007353	0.00025252

DDM

Parameters	ABC	CSA	CS	DE	DSA	GSA	HS	PSO	CMA-ES
RS (Ω)	0.01188791	2.04E-07	6.97E-05	0.012755	1.98E-12	2.24E-02	1.25E-03	2.70E-01	8.77E-18
Rp (Ω)	16.8146454	5.00E+02	448.477	5.031745	5.00E+02	2.45E+02	3.64E+02	4.35E+02	500
IL (A)	3.37079874	2.16E+00	2.164703	3.41E+00	2.16E+00	2.16E+00	2.16E+00	9.38E-01	2.16471
ID1 (A)	1.67E-07	1.66E-11	2.50E-10	4.89E-09	1.74E-15	1.00E-08	9.39E-09	6.64E-09	1.71E-21
ID2 (A)	1.33E-09	3.20E-11	7.17E-09	4.18E-08	2.43E-10	9.98E-09	7.20E-09	1.86E-09	2.43E-10
n1	1.36986811	1.000009475	1.000271	2.454186	1.9889716	1.78140319	1.26138542	1.5581188	1.98855852
n2	310.20159	1.95998006	1.857724	1.266697	1	1.80164641	1.22777934	1.1065305	1
Min RMSE	0.00476202	0.300849656	0.300845428	0.004718	0.3008454	0.30106051	0.30097447	0.3009636	**0.00378198**
Max RMSE	0.00633534	0.301050402	0.300845888	0.004845	0.3008454	0.30564935	0.30159409	0.3014975	**0.00476034**
Average RMSE	0.00501231	0.300961924	0.30084558	0.004725	0.3008454	0.3023613	0.30114073	0.301172	**0.0045456**
Std	0.00026864	3.31744E-05	9.054E-08	8.71E-06	**7.976E-14**	0.00092921	0.0001444	0.0001434	8.7065E-06

$(300\ \mathrm{W/m^2})$ at $T = 25°\mathrm{C}$. In the estimation process, the SDM, as well the DDM models, are used. Table 2, 3, 4 and 5 present the results for the cases of $(1000\ \mathrm{W/m^2})$, $(800\ \mathrm{W/m^2})$, $(500\ \mathrm{W/m^2})$ and $(300\ \mathrm{W/m^2})$, respectively.

Experimental results from Tables 2, 3, 4 and 5 show that the CMA-ES presents the best possible performance; however, CSA and DSA maintain also very good index values. The rest of the algorithms produce results with different performance levels.

One exception, in the results, was the standard deviation in which the lower values have been reached by the CS in the single diode at $(1000\ \mathrm{W/m^2})$, the DE in the double diode at $(800\ \mathrm{W/m^2})$, the CS and DSA at $(300\ \mathrm{W/m^2})$ for the single and double diode, respectively.

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Table 12. Solar cells Module (Multi-crystalline KC200GT) parameters estimation, Mean and Standard deviation for the Single Diode Model (SDM) and Double Diode Model (DDM) at 200 W/m^2.

SDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
RS (Ω)	0.01141702	5.44E-08	1.61E-02	1.05E-02	0.0145769	0.01762537	0.0018854	1.79E-01	0.02447924
Rp (Ω)	147.191212	499.9912692	167.8188	201.0279	339.93184	2.21E+02	1.70E+02	429.52154	24.3117548
IL (A)	1.68087497	2.164709998	1.675382	1.676926	1.6757034	1.41175765	1.68040673	1.6786414	1.68007665
ID (A)	3.78E-07	1.65E-11	7.55E-08	6.07E-07	1.66E-07	9.70E-06	6.38E-06	2.40E-06	4.50E-10
n	1.43443606	1.000000995	1.300344	1.481847	1.3638056	1.91865929	1.75798573	1.6323506	1
Min RMSE	0.00640138	0.300942015	0.3008454	0.006144	0.3008454	0.30114476	0.30098639	0.3011497	**0.00606314**
Max RMSE	0.00965965	0.302323073	0.300845451	0.007015	0.3008454	0.32671827	0.30270375	0.3048593	**0.00681995**
Average RMSE	0.00744433	0.301011783	0.30084541	0.00653	0.3008454	0.30861766	0.30154735	0.3025211	**0.00643948**
Std	0.00077881	0.000243937	1.10173E-08	0.000198	**5.385E-16**	0.00578398	0.00043297	0.0008678	0.00043752
DDM									
Parameters	**ABC**	**CSA**	**CS**	**DE**	**DSA**	**GSA**	**HS**	**PSO**	**CMA-ES**
RS (Ω)	0.02301243	6.55E-08	0.024463	0.022756	0.0240381	1.65E-02	0.02084871	2.29E-02	2.45E-02
Rp (Ω)	257.694441	499.1710598	23.34492	51.2072	3.62E+01	255.333055	402.097715	4.02E+02	24.3117565
IL (A)	1.67617312	2.164709912	1.680472	1.68E+00	1.68E+00	1.60E+00	1.66829732	1.6706903	1.68E+00
ID1 (A)	3.47E-09	1.00E-11	4.50E-10	1.66E-09	6.67E-10	4.74E-11	6.83E-09	1.84E-09	1.47E-21
ID2 (A)	1.08E-09	1.65E-11	2.71E-09	8.54E-10	2.93E-10	7.87E-09	7.08E-09	2.45E-09	4.50E-10
n1	6.73073562	1.92E+00	1.000026	1.062261	1.018037	1.64570227	1.19967205	1.0677641	1.86977567
n2	1.04000367	1.000039816	1.777667	2.290439	1.9428294	1.14876342	1.17225141	1.670724	1
Min RMSE	0.00472589	0.300855771	0.300845424	0.004718	0.3008454	0.30118528	0.30096118	0.3009839	**0.00471636**
Max RMSE	0.00535393	0.301022601	0.300845711	0.004851	0.3008454	0.30648166	0.30158047	0.3015689	**0.00474499**
Average RMSE	0.00494432	0.30095187	0.300845559	0.004725	0.3008454	0.30264489	0.30111403	0.3011762	**0.00472412**
Std	0.00016301	3.00989E-05	7.51683E-08	6.7E-06	**6.492E-14**	0.00130048	0.00014352	0.0001382	6.1847E-06

4.2 Identification of multi-crystalline solar cell D6P

The second experiment considers the parameter estimation of a multi-crystalline solar cell D6P. The identification examines two different solar irradiations $\left(1000\ \mathrm{W/m^2}\right)$ and $\left(500\ \mathrm{W/m^2}\right)$ at $T = 25°\mathrm{C}$, for the Single Diode Module (SDM), double Diode Model (DDM) and the Three Diode Model (TDM). Table 6 and 7 present the results for the cases of $\left(1000\ \mathrm{W/m^2}\right)$ and $\left(500\ \mathrm{W/m^2}\right)$, respectively.

According to the Tables, the CMA-ES obtains the best results in comparison with the others

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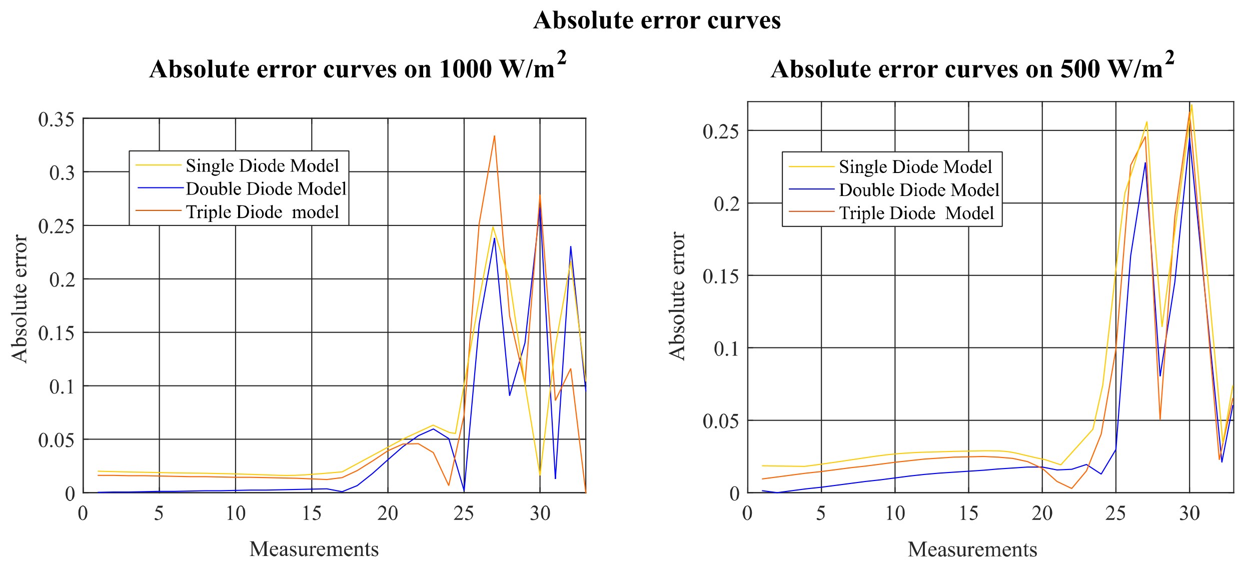

Fig. 4. Absolute error curves generated by the CMA-ES for the D6P100 Multi-crystalline solar cell under two irradiation conditions: 1000 W/m^2 (Condition A) and 500 W/m^2 (Condition B) for the SDM, DDM and, TDM

techniques for the SDM, DDM and TDM models. In case of the standard deviation, the best results were obtained by the ABC in the single diode at(1000 W/m^2), DE in the three-diode model at (1000 W/m^2) and CS in the single and double diode at (500 W/m^2).

4.3 Identification of Multi-Crystalline Module KC200GT

Finally, the third experiment analyzes the parameter estimation of a Multi-crystalline module KC200GT. The identification examines the Single Diode Model (SDM) and the Double Diode Model (DDM) for the conditions of $\left(1000 \text{ W/m}^2\right)$, $\left(800 \text{ W/m}^2\right)$, $\left(600 \text{ W/m}^2\right)$, $\left(400 \text{ W/m}^2\right)$ and (200W/m^2). Table 8, 9, 10, 11 and 12 present the results of each algorithm for the cases of $\left(1000 \text{ W/m}^2\right)$, $\left(800 \text{ W/m}^2\right)$, $\left(600 \text{ W/m}^2\right)$, $\left(400 \text{ W/m}^2\right)$ and (200W/m^2), respectively. Tables 8 and 9 demonstrate that CMA-ES shows competitive results finding the minimum RMSE value in the most of the cases; however, the CS and DE are also able to find a good solution with considerable precision. In the experiments, the CMA-ES obtains the best result for almost all cases, except the standard deviation in several cases such as CS in the single diode model at $\left(800 \text{ W/m}^2\right)$ and $\left(600 \text{ W/m}^2\right)$. On the other hand, the DSA obtain the lower standard deviation for the single and double diode model at $\left(400 \text{ W/m}^2\right)$ and $\left(200 \text{ W/m}^2\right)$.

4.4 Statistical Analysis

For the validation of the obtained results, we proceed to statistically analyze the data acquired for each EC technique during the estimation process. The study combines the Wilcoxon test and the Bonferroni correction. The Wilcoxon analysis [49], [50] measure the difference between two related methods. This test considers the 5% of significance level over the Average RSME values (*p*-value, 0.05). Since the results reveal that the alleged best algorithm is the CMA-ES, the comparison considers seven groups for the test: CMA-ES *vs* ABC, CMA-ES *vs* CSA, CMA-ES *vs* CS, CMA-ES *vs* DE, CMA-ES *vs* DSA, CMA-ES *vs* HS and CMA-ES *vs* PSO. In the Wilcoxon test, the

Table 13. Wilcoxon test for the SDM and DDM for the Mono-crystalline cell and the Multi-crystalline Module and SDM, DDM and TDM for the Multi-crystalline cell at different irradiation conditions after the Bonferroni correction

C60 Mono-crystalline									
IR		**CMA-ES vs**							
		ABC	**CROW**	**CS**	**DE**	**DS**	**GSA**	**HS**	**PSO**
1000	SDM	1.43E-14 ▲	1.43E-14 ▲	1.28E-14 ▲	1.28E-14 ▲	1.51E-13 ▲	1.33E-14 ▲	1.39E-14 ▲	1.43E-14 ▲
	DDM	1.01E-05 ▲	0.100873 ▲	1.53E-14 ▲	1.64E-14 ▲	5.2E-05 ▲	1.45E-14 ▲	1.14E-13 ▲	6.90E-08 ▲
800	SDM	1.66E-14 ▲	1.66E-14 ▲	1.30E-14 ▲	1.28E-14 ▲	1.03E-12 ▲	1.34E-14 ▲	1.58E-14 ▲	1.43E-14 ▲
	DDM	1.76E-05 ▲	0.176388 ▲	1.35E-14 ▲	1.51E-14 ▲	1.12E-07 ▲	1.48E-14 ▲	1.46E-14 ▲	7.21E-08 ▲
500	SDM	1.43E-14 ▲	1.43E-14 ▲	1.29E-14 ▲	1.29E-14 ▲	3.58E-13 ▲	1.42E-14 ▲	1.63E-14 ▲	1.43E-14 ▲
	DDM	1.29E-06 ▲	0.012867 ▲	1.24E-14 ▲	1.39E-14 ▲	1.74E-05 ▲	1.50E-14 ▲	1.45E-14 ▲	1.56E-08 ▲
300	SDM	1.44E-14 ▲	1.57E-08 ▲	1.44E-14 ▲	1.67E-12 ▲	2.22E-12 ▲	1.35E-13 ▲	1.54E-14 ▲	1.31E-14 ▲
	DDM	4E-09 ▲	1.44E-14 ▲	1.38E-14 ▲	1.39E-14 ▲	1.44E-14 ▲	1.28E-14 ▲	1.53E-14 ▲	1.36E-14 ▲
D6P100 Multi-crystalline									
IR		**CMA-ES vs**							
		ABC	**CROW**	**CS**	**DE**	**DS**	**GSA**	**HS**	**PSO**
1000	SDM	2.81E-14 ▲	9.96E-06 ▲	1.99E-06 ▲	5.84E-04 ▲	1.74E-04 ▲	1.44E-14 ▲	1.44E-14 ▲	1.44E-14 ▲
	DDM	5.04E-04 ▲	1.28E-12 ▲	2.08E-12 ▲	1.56E-09 ▲	1.38E-11 ▲	1.44E-14 ▲	2.22E-12 ▲	2.22E-12 ▲
	TDD	8.66E-04 ▲	3.47E-04 ▲	6.91E-08 ▲	5.10E-05 ▲	7.98E-09 ▲	1.43E-14 ▲	2.92E-12 ▲	2.92E-12 ▲
500	SDM	4.08E-14 ▲	6.56E-04 ▲	1.24E-14 ▲	1.23E-04 ▲	1.59E-04 ▲	1.44E-14 ▲	1.44E-14 ▲	1.44E-14 ▲
	DDM	3.44E-05 ▲	7.91E-14 ▲	1.44E-14 ▲	1.69E-11 ▲	1.64E-13 ▲	6.73E-09 ▲	1.11E-12 ▲	1.11E-12 ▲
	TDDD	1.06E-14 ▲	1.06E-14 ▲	1.06E-14 ▲	1.06E-14 ▲	1.06E-14 ▲	1.06E-14 ▲	1.06E-14 ▲	1.06E-14 ▲
Mod. kc200gt Mono-crystalline									
IR		**CMA-ES vs**							
		ABC	**CROW**	**CS**	**DE**	**DS**	**GSA**	**HS**	**PSO**
1000	SDM	2.08E-11 ▲	1.36E-14 ▲	2.36E-11 ▲	7.18E-04 ▲	6.55E-08 ▲	2.85E-14 ▲	1.28E-14 ▲	2.44E-14 ▲
	DDM	1.94E-14 ▲	1.63E-14 ▲	1.63E-14 ▲	2.79E-05 ▲	1.55E-06 ▲	1.51E-14 ▲	1.24E-14 ▲	2.44E-14 ▲
800	SDM	1.58E-11 ▲	1.35E-14 ▲	2.44E-11 ▲	4.05E-04 ▲	7.44E-08 ▲	2.75E-14 ▲	1.25E-14 ▲	2.54E-14 ▲
	DDM	2.81E-14 ▲	1.45E-14 ▲	1.44E-14 ▲	9.31E-05 ▲	2.14E-06 ▲	1.61E-14 ▲	1.22E-14 ▲	2.50E-14 ▲
600	SDM	6.35E-14 ▲	1.36E-14 ▲	2.44E-11 ▲	4.73E-04 ▲	5.44E-08 ▲	3.14E-14 ▲	1.30E-14 ▲	2.49E-14 ▲
	DDM	1.55E-14 ▲	1.44E-14 ▲	1.44E-14 ▲	1.13E-05 ▲	1.35E-06 ▲	1.71E-14 ▲	1.24E-14 ▲	2.44E-14 ▲
400	SDM	1.94E-12 ▲	1.40E-14 ▲	2.44E-11 ▲	2.71E-04 ▲	7.84E-08 ▲	2.94E-14 ▲	1.25E-14 ▲	2.44E-14 ▲
	DDM	1.44E-14 ▲	1.49E-14 ▲	1.44E-14 ▲	7.47E-05 ▲	1.51E-06 ▲	1.55E-14 ▲	1.23E-14 ▲	2.42E-14 ▲
200	SDM	8.1E-12 ▲	1.33E-14 ▲	2.44E-11 ▲	2.72E-04 ▲	6.74E-08 ▲	3.12E-14 ▲	1.21E-14 ▲	2.41E-14 ▲
	DDM	3.27E-14 ▲	1.41E-14 ▲	1.44E-14 ▲	2.13E-05 ▲	1.46E-06 ▲	1.89E-14 ▲	1.27E-14 ▲	2.49E-14 ▲

null hypothesis is considered as there is not difference enough between approaches, and as an alternative hypothesis if exists significance difference between both approaches.

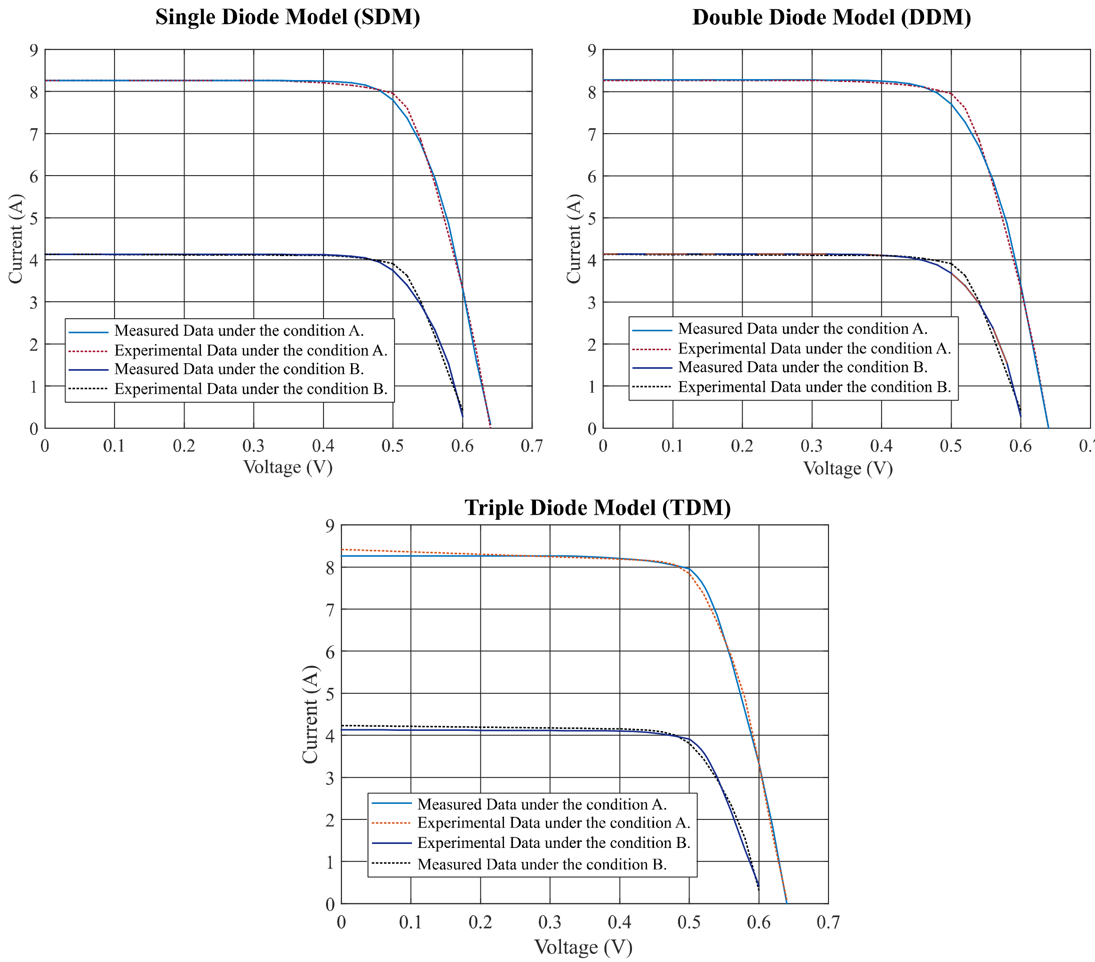

Fig. 5. Comparison of *I-V* characteristic between the measured data and the approximate model determined by CMA-ES for the D6P100 Multi crystalline solar cell under two irradiation conditions: 1000 W/m^2 (Condition A) and 500 W/m^2 (Condition B)

On the other hand, as the number of elements in the comparison is high, the possibility to produce an error type 1 increases. In order to avoid this problem, the significance value (*p*-value) must be readjusted using the Bonferroni correction [51, 52].

Therefore, once we have the *p*-values obtained by Wilcoxon method, they are compared with the new *n*-value calculated by the Bonferroni test, if is *n*>*p* the null hypothesis is rejected, avoiding the error type 1. With the intention to simplify the analysis of the results, in table 13, the symbols ▲, ► and ▼ are used.

Here ▲ indicates that CMA-ES performs better than its respective counterpart, ▼ means that CMA-ES performs worse than the compared technique, and ► symbolizes that there is no significant difference between the compared techniques.

The *n*-value determined by Bonferroni correction considering the value of 0.00139. Table 13 presents the result of the statistical study. It analyzes the indexes of all estimation process for the solar cells.

According to Table 13, the CMA-ES outperforms (▲) the rest of the techniques used in this study for the three equivalent models regarding the statistical analysis.

4.5 Response Graphics

Figure 4 shows the absolute error curves between the measured data and the values determined by the CMA-ES model under 1000 W/m^2 and 500 W/m^2 for the SDM, DDM and TDM. In figure 5, the *I-V* characteristics between the measured data and the approximate model found by the CMA-ES are shown. This figure considers two different conditions. In the condition A, the irradiation is set in 1000 W/m^2 while for the condition B, the irradiation is 500 W/m^2. The D6P100 Multi-crystalline solar cell is used to represent the responses for the SDM, DDM and TDM.

5 Conclusions

Several proposals of evolutionary computation (EC) methods to estimate the parameters of solar cells have been reported in the literature. However, most of them report only a single EC technique considering a minimal number of solar cell models. In this work, a comparative study of solar cells parameter estimation is discussed. In the comparison different EC Techniques are used, such as Artificial Bee Colony (ABC), Crow Search Algorithm (CSA), Cuckoo Search (CS), Differential Evolution (DE), Differential Search (DSA), Gravitational Search Algorithm (GSA), Harmony Search (HS), Particle Swarm Optimization (PSO) and Covariant Matrix Adaptation with Evolution Strategy (CMA-ES). The comparison was developed over three equivalent solar cell models, the Single Diode (SDM), Double Diode Model (DDM) and Three Diode Model (TDM) using a Mono-crystalline solar cell for the SDM and DDM, a Multi-crystalline solar cell for the SDM, DDM and TDM and a solar cell module for the SDM and DDM.

The estimation of parameters in solar cells represents a complex task due to their dimensionality and non-linearity of the generated error surface. After comparing the capabilities of each EC technique, it has found that the CMA-ES outperformed the rest of the techniques regarding minimum and average root mean square error (RMSE). In the case of the standard deviation, the best results were distributed among CMA-ES, CS, DE, and DSA. The results have been validated through a statistical study that combines the Wilcoxon test and the Bonferroni correction.

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